Learning Style Recognition Based on Adjustable Multiple Layers FCM

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***Abstract*-Identification of learning styles supports Adaptive Educational Hypermedia Systems compiling and presenting tutorials custom in cognitive characteristics of each individual learner. This work addresses the issue: identifying the learning style of students, following the Kolb's learning cycle. To this purpose, we propose a three-layer Fuzzy Cognitive Map (FCM) in conjunction with a dynamic Hebbian rule for learning styles recognition. The form of FCMs is designed by humans who determine its weighted interconnections among concepts. But the human factor may not be as reliable as it should be. Thus, a FCM model of the system allows the adjustment of its weights using additional learners' characteristics such as the Learning Ability Factors. In this article, two consecutively interconnected FCM (in the form of a three layer FCM) are presented. The schema's efficiency has been tested and compared to known results after a fine-tuning of the weights of the causal interconnections among concepts. The simulations results of training the process system verify the effectiveness, validity, and advantageous characteristics of those learning techniques for FCMs. The online recognition of learning styles by using three-layer Fuzzy Cognitive Map improves the accuracy of recognition obtained using Bayesian Networks that uses quantitative measurements of learning style taken from statistical samples. This improvement is due to the fuzzy nature of qualitative characterizations (such as learning styles), and the presence of intermediate level nodes representing Learning Ability Factors. Such factors are easily recognizable characteristics of a learner to improve adjustment of weights in edges with one end in the middle-level nodes. This leads to the establishment of a more reliable model, as shown by the results given by the application to a test group of students.**

Keywords-Adaptive Educational Hypermedia Systems; LO Standards; LO Interoperability; Learning Style

I. INTRODUCTION

With the development of computer networks and the growth of information that is stored on Web servers, the requirement for adaptive data search and retrieval becomes essential. The demand for adaptive data retrieval reflects on e-learning technologies as well. The field of Adaptive Educational Hypermedia Systems (AEHS) became an active research area as the community became aware of the benefits of adaptation. In AEHS the adaptation process includes two steps. The first step concerns the detection of individual needs of learners. The second refers to the courses' adaptation according to the identified learner's needs. Adaptive Intelligent Tutoring Systems (AITS) (Pipatsarun P., Jiracha V.**,** 2010) and AEHS offer Learning Objects (LO) adapt to the user's learning factors such as computer proficiency, technology acceptance, class interaction, attitude, class satisfaction, user satisfaction, technology and Learning Styles (LS), which are considered to be as the most important . AEHS build a model of the goals, preferences and knowledge altogether with learning factors of each individual user, and use this model throughout the interaction with the user, in order to adapt content appropriately to the needs of that user. A consequence raises the need of recognition and measurement of such learning factors. In this paper the main goal is to propose an efficient tool, for recognition of the learner's learning style. Learning styles are believed to influence students' ability to learn [Loo, R. 2004.].

We are all individual persons and, as such, we have individual preferences and styles of learning. Although, many research studies have taken place up-to-date, they have not given proof of sound and solid evidence on the impact of LSs on teaching and learning. Personality traits, intellectual abilities and fixed traits which are said to form LSs (Coffield, et al., 2004:1)

When the students gain knowledge of their LSs, then they are expected to increase their self-consciousness about their strong and weak points as learners. As Green (2002) mentions: "Knowledge of learning preferences can help learners exploit opportunities to learn though activities that match them well with their preferred style".

Dunn (1990, 15) supports that: "When students are taught with approaches that match their preferences… they demonstrate statistically higher achievement and attitude test scores，even on standardized tests than when they are taught with approaches that mismatch their preferences". According to the principle of student-centered instruction all teaching material should be organized and offered to the student according to his needs. All teaching actions take in consideration the student and how he/she can learn better and more efficiently. The teacher adjusts his strategies and methods so that he can help his students achieve successful learning. Therefore the teacher should offer the information in a way that responds in the best possible way to his students' needs (Mitropoulou, 2008:52-53). "Tutors carefully select a good range of learning materials, directly relevant to the needs, interests, and LSs of the learner" (ALI 2002a, 21)

People differ dramatically in how quickly and easily they learn new material. Each one of us is a different person; therefore, each student perceives information in a different unique way and elaborates it differently from the others. There are various types of students' visual, acoustic, kinesthetic and the teaching material that should be presented according to their type.

According to the principle of individualized instruction each student is a different personality, so the teacher should take into consideration that each student differs from the other and the individual characteristics and abilities of each student, which form his LS e.g. interests, inclinations, cognitive

development (Manos, 1993:188) That is, this principle emphasizes the intellectual abilities and particularities of each student (Flouris, 1986:149). Teachers should first diagnose their students' LSs and then organize instructional procedure (methods, strategies, teaching and learning approaches) (Coffield, et al., 2004:1). However, it is very hard, if not unrealistic, for teachers to change their teaching style to accommodate to the LSs (from 4 up to 30) of their students in each class (Reynolds, 1997, 121) because then would have to respond to all learning types of students: visual, verbal, acoustic, inductive, deductive, reflective, active, sequential, conceptual, concrete. Thus, the planning of teaching strategies should proceed over the students' LSs, which could be then used by the teachers to modify their approach (Coffield, et al., 2004:43). Instead this can be achieved efficiently and successfully with the use of AEHSs.

This is supported by the principle of modification of the initial teaching material, according to which the teaching material should be modified, so as to respond to the individual needs of each student, that is his LS (Mitropoulou, 2008:57-58). Thus the AEHS can provide this modification to adjust to the learning needs of the students and "produce an individual plan of activities based on the specific needs of each student" (ALI 2003b, 35-36).

It is clear, that teachers should pay attention not only to the students' differences, as individual personalities, but also to the "teaching-learning environment" (Coffield, et al., 2004:38). Thus, the teachers, in order to enhance the learning of all the students LS, they should change their instructional attitudes accordingly (Coffield, et al., 2004:41).

One theory often promoted to improve learning efficiency is LS, supporting that people learn best when their particular LSs are matched to correspondingly suitable learning environments (Coffield, Moseley, Hall, & Ecclestone, 2004; Ford & Chen, 2001; Pheiffer, Holley, & Andrew, 2005). Many researchers agree on the importance of modeling and using individual traits, but there is little agreement on which features can and should be used, or how to use them. One illustrative example here is the work on adapting to the individual's LS in educational hypermedia. Several systems that attempt to adapt to LS (Carver et al., 1996; Danielson, 1997; Gilbert and Han, 1999; Specht and Oppermann, 1998) have been developed, however it still isn't clear which aspects of LS are worth modeling, and what can be done differently for users with different styles (Brusilovsky, 1996). Other examples which implement different aspects of the Felder-Silverman Index of LSs are WHURLE, (Moore, Brailsford, & Stewart 2001; Brown & Brailsford, 2004) and ILASH (Bajraktarevic, Hall, & Fullick, 2003). The development of an adaptive hypermedia interface, which provided dynamic tailoring of the presentation of course material based on the individual student's LS, was part of the research work by Carver Jr et al (Carver Jr, Howard, & Lane, 1999). By tailoring the presentation of material to the student's LS, authors believe students learned more efficiently and more effectively. Students determine their LS by answering a series of 28 questions. These forms were based on an assessment tool developed at North Carolina State University based on B.S. Solomon's and Felder's Inventory of LSs. In iWeaver the Dunn & Dunn model is applied (Wolf, 2003). LS theory has become quite popular commercially, but predictive validity studies show that empirical support for the theory is weak (Coffield et al., 2004). The authors of this study consider that Web Training Systems that make use of LS theories will prove the validity (or inadequacy) of such theories throughout the extensive application of evaluation procedures and the production of significantly large amount of data.

Several existing theoretical models help to explain LS preferences; however, for the purpose of this study, the model developed by D. Kolb was used. The authors of this study believe that no style is considered better than another. The methodology in this work is applicable with some modifications, to other LS classifications, as well. The reader will find more information about Kolb's LS theory in section 2 (2.1).

As mentioned above, LS recognition is a complex situation to be applied in class. A teacher has to analyze every single student's cognitive characteristics and then he has to apply different content presentations tailored to the needs of each of them. As a human the teacher may not handle such multitasking work in class. Nowadays the development of computing and artificial intelligence methodology is recognized as an important requirement in complex situations such as pattern recognition, medical diagnosis decisions, or LS recognition. Researchers attack to such problems using various methodologies. Among them, one recognizes Bayesian networks and fuzzy logic techniques. Bayesian networks and cognitive networks are useful because of their causal inference in intelligent systems (Liu Z. Q., 2001). In terms of LS recognition via Bayesian networks, one may say that the method is based on statistical valorization of concentrated information to predict their respective properties for each new user of the system (Botsios, Georgiou, & Safouris, 2008). On the other hand, fuzzy logic techniques, transform qualitative characterizations of a subject to measurable quantitative ones that are easily treatable by computers (Georgiou & Makry, 2004), (Georgiou, D. A., & S. D. Botsios., 2008). Looking forward to improve the LS online recognition methodologies, we use a three layer Fuzzy Cognitive Map schema. As far as cognitive maps provide a useful tool to describe existing cause-effect relationships between cognitive and learning characteristics, Fuzzy Cognitive Map (FCM) became a soft computing tool which can be considered as a combination of fuzzy logic and neural networks techniques. A FCM, due to the way it is constructed, integrates the accumulated experience and knowledge on the causal relationship between factors, characteristics, and components of the system. The development of a FCM requires the specification of the signs and magnitudes of the relevant causal relationships by one or more experts based on subjective estimates of the causal relationships (Osei Bryson, K. M., 2004). However, determination of the magnitude is often problematic, and so raises the need to provide an effective means for the generation of consistent estimates of the magnitude of each causal relationship. In fact, FCM uses human experts that know the system and its behavior under different circumstances [Georgopoulos, V. C., G. A. Malandraki, & C. D. Stylios., 2003]. Using 3 Layers FCM for LS recognition we improve its accuracy and allow the system's configurability. This is a result of the middle layer nodes representing learning ability factors (LAF) that are easily recognizable by humans. In the presence of LAF the system becomes more sensitive to the accumulation of human experience than ordinary FCM. For example, application of the proposed LS recognition method to groups that differ in

culture or demographic origins may be a reason to adjust the system properly (Ogbu J.U., 1992), (Joy S., Kolb D.A., 2008).

The study ends with the evaluation of the system's accuracy. The evaluation is based on responses to Kolb's LS inventory given online by a test group of 102 university students. The very same set of responses used in (Botsios, Georgiou, & Safouris, 2008), where the accuracy of the Bayesian network model has been indicated. In this paper the evaluation of the model's accuracy is based on the comparison to Bayesian network model, to be proved more accurately due to a dynamic Hebbian rule application.

This paper is structured as follows. A theoretical background (in section Ⅱ) provides necessary information that supports the reader to understand both the model and its application. In section Ⅲ, an extensive description of the model appears. Moreover, some observations are presented related to system's efficiency. Initially, the system operated using weights taken from a theoretical interpretation of the LAFs and LSs relational map. This phase of the study resulted LS recognitions "close enough" to the expected ones, as they appear from the application of D. Kolb's inventory. Then, using the users' LAF descriptions, the weights adjusted to end with more accurate results. Finally, in section 4 the conclusion and a proposal for future work ends this work..

II. THEORETICAL BACKGROUND

A. Kolb's Learning Cycle

Learning theorists suggested certain LS classifications (Dunn & Dunn, 1990), (Felder & Silverman 1988), (Honey & Mumford 2000). One model of LSs that has generated a significant amount of research is that of David Kolb (Kolb 2000) who, in his research, attributes four roles to the teacher ('facilitator'): "communicator of information, guide or taskmaster, coach or helper, and role model". (p. 17). As Kolb (1984) supports "the aim is to make the student self-renewing and self-directed; to focus on integrative development where the person is highly developed in each of the four learning modes: active, reflective, abstract, and concrete. Here, the student is taught to experience the tension and conflict among these orientations, for it is from the resolution of these tensions that creativity springs". (p. 203)

According to Kolb (1999) LSs are not "fixed personality traits but flexible stable learning preferences". For Kolb the learning cycle is a graph representing his experiential learning theory, which aims to provide a well-defined frame for the "design and management of the learning experiences", which are transformed into concepts, which, in turn, are used for the selection of new experiences thus, contributing to the students' development. Kolb (1999) claims that "all four phases of the cycle are necessary for effective learning", however admitting that "different learners start at different places in this cycle". (p.3) There are different attitudes of the researchers towards LSs inventories, others being for and others against. For those in favor, LSs inventories allow a simple and quick student differentiation and can help to a transformation of "all levels of education", while, for those against, LSs inventories are considered "unreliable and invalid" and they do not use them (Coffield, et al., 2004:44).

Besides exploring foundations posed by Dewey, Lewin and Piaget for experiential learning, Kolb presented a model of four particular elements, which together constitute an optimal learning process. While teaching management students he noticed that some students preferred learning through experiences whereas others preferred the traditional classroom lecture. His subsequent theory of experiential learning proposed that, while learning, people resolved conflicts between a) active experimentation and b) reflective observation along one axis and between c) concrete experience and d) abstract conceptualization along another axis. His model yielded four quadrants and he stated that, over time, people developed LS preferences that can be categorized into one of the four quadrants.

The model is widely known (and depicted) as a learning cycle and Kolb also used its elements to identify 4 LSs, each corresponding to the spectrum between 2 elements. The Diverger, who supposedly prefers to learn through concrete experience and reflective observation. In what follows we focus on the 4 core elements and use them to illustrate and discuss activities in different teaching and learning environment. The model is represented in a two dimensions graph, as shown on Fig. 1.

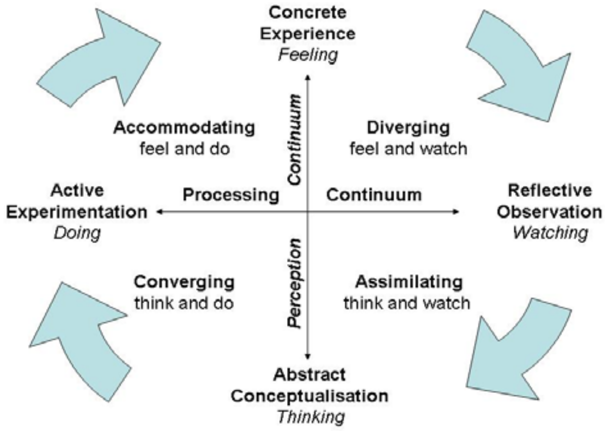

Fig. 1 D. Kolb's learning cycle

Whereas commercially popular pedagogical tools have been generated by Kolb's work, empirical support for constructive and predictive validity has been lacking (Coffield et al., 2004).

As noted by Brusilovsky in his 2001 work, several systems that attempt to adapt to LS had been developed, however it was still not clear which aspects of LS are worth modeling, and what can be done differently for users with different styles (Brusilovsky, 2001).Since then efforts have been made and a quite large number of surveys have been published that remark the benefits of adaptation to LS. There are also a number of attempts to implement LS in AEHSs. ACE (Adaptive Courseware Environment) is a www-based tutoring framework, which combines methods of knowledge representation, instructional planning, and adaptive media generation to deliver individualized courseware over the www. Experimental studies within ACE showed that the successful application of incremental linking of hypertext is dependent on students' LS and their prior knowledge (Specht & Oppermann, 1998).

B. Learning Style Recognition

LS recognition is considered to be one among others parameters in AEHSs. Therefore, such systems should be able to recognize (or estimate) LS. The term is widely used in education and training and refers to a range of constructs from instructional preferences to cognitive style (Farnham-Diggory,

1992). The issue of learner's LS estimation in the scope of providing instruction tailored to his / her educational needs has been addressed several times in the literature.

LS recognition may be succeeded by asking a number of suitable questions. To this purpose questionnaires and inventories have been developed. Cognitive scientists introduced a wide range of LS Inventories (LSI) and related questionnaires have been proposed to be serving as LS recognition tools. The LSI has been the subject of analyses by (Willcoxson & Prosser, 1996; Yahya 1998; Loo & Thorpe 2000; Loo 2004). Their findings gave some support to the LSIs' two-dimensional structure; however they did not consider LS in relation to other constructs. Kolb's model is particularly elegant, since it offers both a way to understand individual people's different LSs, and also an explanation of a cycle of experiential learning that applies to the vast majority of humans. In their research, Graf and Kinshuk (2007) show how cognitive traits and LSs can be incorporated in web-based learning systems by providing adaptive courses. The LS estimation in their work is made by a 44-item questionnaire based on Felder-Silverman LS model (Graf & Kinshuk, 2007). Moreover, empirical studies were conducted on two educational systems (Flexi-OLM & INSPIRE) to investigate learners' learning and cognitive style and preferences during interaction (Papanikolaou et al., 2006). The Index of LSs questionnaire was used to assess the style of each participant according to the four dimensions of the Felder-Silverman LS model. It was found that learners do have a preference regarding their interaction, but no obvious link between style and approaches offered, was detected to investigate methods for online recognition of LSs.

As other researchers did, Kolb (Kolb, 1999) developed a LS Inventory (LSI) to measure peoples' individual LSs. By knowing the LSs of their students and by creating learning environments matched to those LSs, educators could enhance learning. The preference is diagnosed by analyzing subject's responses in a number of appropriate questions. Kolb made a self-test LSI that can reveal the weak and strong points of learning.

In what concerns online LS estimation, a BN is capable of classifying learners in a predefined set of classes. An expert system takes advantages on previously accumulated knowledge, and thus is more accurate than LS direct estimation, i.e. an estimation based only on a single user's responses (Botsios, Georgiou, & Safouris, 2008). Furthermore, in this first attempt the Fault Implications Avoidance Algorithm (FIAA) has been introduced to the purpose of reducing the unnecessary responses to LSI.

Later, in the same direction of online LS estimation, formal FCM schemata (Georgiou & Makry, 2004) and (Georgiou, D. A., & S. D. Botsios., 2008) have been applied.

C. Learning Ability Factors

Stake sought to investigate the possibility that "there is a general learning ability, independent of what intelligence tests measure that is influential, by itself or jointly with other factors in every learning situation" (Stake, 1958). Stake constructed a number of short-term learning tasks and determined, for each subject and task, parameters of the learning curve. These parameters constituted variables in a factor analysis battery that also included scores on a variety of factor reference tests, measures of intelligence, and school grades, for a 240 children test group. Stake obtained 14 oblique first-order factors. The design of Alison's (1960) study was similar to that of Stake, in that it employed a series of learning asks to define learning ability parameters, and included a series of factor reference test. Allison concluded that (1) learning ability is multidimensional, containing several factors that are dependent upon the psychological processes involved in the learning task and the content of learning object to be learned, and (2) measures of learning and measures of aptitude and achievement have factors in common with each other. Since then, many researchers enriched scientific knowledge with new contributions to the subject of learning abilities and the role they play in Learning Theories.

Learning abilities enable students to achieve the learning outcomes of a course. As an illustration of the complexity of this undertaking, learning abilities are easier to observe, describe, research and integrate into other tasks than LSs. Some of the learning abilities in the work place allow the student to demonstrate various learning activities, such as self-directed learning, mentoring, networking, asking questions, and receiving feedback (Berg & Youn, 2008). Basic learning ability types are: creation, experimentation, debate, reception, imitation, exercitation, exploration, and reflexion (Verpoorten, Poumay, & Leclercq, 2007). Levy (2006) extended the conceptual map of general human activity proposed by Hasan and Crawford to online learning activity (Levy 2006). He defined online learning activity as "an educational procedure designed to stimulate learning by online experience utilizing online learning systems and tools". Learning Ability Taxonomy identifies 72 possible learning tasks including: analyzing, creating, explaining, listing, refining, and summarizing.

This diversity of learning tasks suggests that it can be challenging for educators to organize LAFs successfully, to the purpose of better understanding cognitive characteristics of their students (Kerawalla et al., 2009). In literature it can be found of a wide variety of LAFs that have been introduced by cognitive scientists Jonassen(1992), Honey&Mumford (1992).

LAFs serve as a medium to categorize the learner's cognitive preferences. It has been shown (Kolb, 1984) that LAFs map out on LSs. It also appears that the degree of relation varies in terms of the LAF's influence on a certain LS. Such relations may be influenced by factors such as cultural environment, learner's age, or psychological status influence.

Since there is a wide variety of learning ability descriptions, we introduce a map of learning abilities on a smaller number of characterizations: the subset of LAFs that will be used in this paper. An example of relations between learning activities and LAFs is represented in Table Ⅰ.

TABLE I RELATIONS BETWEEN LEARNING ACTIVITIES AND LAFS USING LINGUISTIC VARIABLES: VERY STRONG (VS), STRONG (S), MODERATE (M), WEAK (W) AND VERY WEAK (VW)

		Analyzing	Creating	Explaining	Listing	Refering	Summarizing	Self direct learning	Mentoring	Networking	Asking Questions	Receiving Feedback
LAF	Experimentation	s	vs						s	s	s	
	Influencing People			vs				vw	vs	vs		
	Implementing Solution		s			vs	vs					
	Emotion/Intuition		m					s				
	Scientific/Analytic	vs			vs		s				vs	

D. Fuzzy Cognitive Maps

FCMs are the fuzzified version of cognitive maps, which can represent experts' beliefs (Huff, 1990). The objective of Cognitive Maps is to examine whether the state of one element is perceived to have an influence on the state of the other (Lee et al., 2002). FCMs have been proved a useful tool for exploring and evaluating the impact of different inputs to fuzzy dynamical systems that involve a set of objects (e.g. processes, policies, events, values) and causal relationships between the objects. FCM enable experts to graphically represent factual and evaluative objects, and relevant causal relationships between the objects. Therefore, FCMs can also represent experts' beliefs as a dynamic relational map. Necessarily, the relations are poor approximations of complex dynamic systems and some account has to be made for uncertainty at this level of description. In most of the works, causal relationships in cognitive maps are predefined. An integrated process for generating consistent subjective estimates of causal relationships magnitude appeared in (Osei-Bryson, 2004) allows the extensive FCM use.

A wide variety of methodologies based on fuzzy sets, fuzzy relations and fuzzy control have appeared in literature. FCMs have been used to model a variety of practical problems including water desalination (Hussein & Ismael, 1995), telecommunications (Lee & Han 2000), or analysis of electric circuits (Styblinski & Meyer, 1988). Among them, one can isolate certain methods which can be applied on the diagnosis of mental disorders, language impairments or learning disabilities (Georgopoulos, Malandraki, & Stylios, 2003). An FCM that served as a basis for LS online estimation (Georgiou & Botsios, 2008) can be considered as the basis for the results that follow. In that work no forethought was taken to allow experts interference to the purpose of adjusting the outcomes.

FCM representation is as simple as an oriented and weighted compact graph. For example, the FCM, which is depicted in Fig. 2, consists of seven nodes which represent an equivalent number of concepts. Concepts represent key factors and characteristics of the modeled system and stand for inputs, outputs, variables, states, events, actions goals, and trends of the system. Each concept C_i is characterized by a numeric value V (C_i) which indicates the quantitative measure of the concept's presence in the model. Each two distinct nodes are joined by at most one weighted arc. The arcs represent the causal relationships of connected concepts. The degree of causality of concept C_i to concept C_j is expressed by the value of the corresponding weight w_{ij}. Experts describe this degree using linguistic variables for every weight, so this weight w_{ij} for any interconnection can range from –1 to 1.

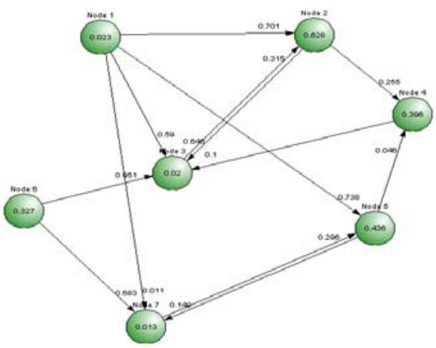

Fig. 2 An example of FCM

There are three types of causal relationships expressing the type of influence among the concepts, as they represented by the weights w_{ij}. Weights can be positive, negative or can also be zero. Positive weight means the increasing influence a concept implies to its adjacent concept of the graph, as on the other hand, negative weight means that as concept C_i increases, concept C_j decreases on the w_{ij} ratio. In absence of relation between C_i and C_j, the weight w_{ij} equals zero.

At the step n+1 the value $V^{n+1}(C_i)$ of the concept C_i is determined by the relation

$$V^{n+1}(C_i) = f(\sum_{\substack{j=1 \\ i \neq j}}^{k} w_{ji} V^n(C_j)) \qquad (1)$$

where $V^n(C_i)$ is the value of the concept C_i at the discrete time step n. Since there is a vast and sometimes controversial variety of expert's opinion on the weight with which a concept influences another concept, it is worthwhile to introduce a suitable algorithm for the adjustment of the set of weights in FCM. As it has been already mentioned, the numerical values of weights have to lay in the interval [-1, 1], as the FCM will converge either to a fixed point, or limit cycle or a strange attractor (Dickerson & Kosko, 1993). In the case in hands, where the FCM is called to support decision making on learner's style, it is better to converge to a certain region which is suitable for the selection of a single decision.

Function *f* is a predefined threshold function. Generally two kinds are used in the FCM framework. Either *f(x)* = tanh*(x)* that is used for the transformation of the content of the function in the interval [-1, 1], or a uni-polar sigmoid function. We use the uni-polar sigmoid function, as we want to restrict values of concepts between 0 and 1. The function is given by the relation

$$f(x) = \frac{1}{1+e^{-\lambda x}} \qquad (2)$$

where $\lambda > 0$ determines the steepness of the sigmoid.

E. Fault Implication Avoidance Algorithm

In this study the Kolb's LS Inventory (KLSI) was applied. Dr. David Kolb introduced KLSI that includes 8 items, i.e. 8 questions about one's personal way of learning. Each item in KLSI consists of 4 statements that appear in every possible combination of pairs, i.e. six pairs of statements. Therefore, there are six choices and the student is asked to choose one of the two statements for every pair. Depending on the selection of each statement, it is possible, due to implication reasons, to determine some future selections. The following example describes a practical application.

Let us consider three selection pairs consisting of the statements (a), (b), and (c). Logical implication determines that once the statement (a) is chosen between (a) and (b) in the first selection pair, and (b) is chosen between (b) and (c) in the second selection pair, the choice of (a) instead of (c) is obligatory (Table Ⅱ). As the first two selections lead to (a)>(b)>(c) order of preference. Alternatively, reverse choices in pairs 1 and 2 ((b) and (c) instead of (a) and (b) correspondingly) leads to the order (c)>(b)>(a). In every other combination of choices in pairs 1 and 2, no logical implication appears and pair 3 remains open to choose from its statements. At this point a question arises: What if a selection in pair 3 can better represent the user's preference than pair 1 or 2, do

not allow a choice to be made in pair 3 and moreover those choices lead to wrong order of (a) and (c). The answer is that pair 3 can only be "locked", ranking statements (a) and (c) in a wrong way, in the very rare case the user's choices in pairs 1 and 2 are both against his/her preferences. In case were only one choice from pairs 1 or 2 is against the user's real preferences, pair 3 remains "unlocked" waiting the user's selection. Obviously, the probability of two sequential "wrong" choices is considerably smaller than making one "wrong" choice even in cases of statistical dependence.

TABLE II EXAMPLE OF FAULT IMPLICATION AVOIDANCE ALGORITHM

pair	statement	input method
1	a	user selection
	b	
2	b	user selection
	c	
3	a	automatic selection

Analogously, for more than three selections, the final ranking can be reached by responding to a subset of the set of selections pairs. A more complex example with 6 selection pairs, which is the case of KLSI, can be found in previous work (Botsios, Georgiou, & Safouris, 2008).

In the printed KLSI there are no such possibilities, as the student has to deal with every single selection pair in the item. It has been noticed that some students who succeeded an early final ranking, conflict it by their late responses. The original printed KLSI reduces fault logical implication influence on the final estimation by repeating the ranking procedure 8 times (8 items). Taking advantage of the computer capabilities the proposed FIAA makes a step further to face possible fault logical implications.

I. THE MODEL

A. Description

In what follows, we present the integration of three layers of LS estimation (LSI statements, LAFs and LSs) in a 3L-FCM implementation. The proposed 3L-FCM is a tripartite graph that describes causal relationships between consecutive layers. Let us now consider three layers of nodes. In tripartite graphs vertices connect nodes of subsequent layers, avoiding any connection between nodes of the same layer. The upper layer consists of all the statements one can find in KLSI. Since it contains 8 items of 4 statements each, the upper layer contains 84=32 nodes Ci, i=1, 2…, 32 representing the total number of statements in KLSI. In order to save space, in Fig. 3 we present a part of the 3L-FCM that concerns the statements A, B, C and D of only one item of KLSI, In the middle layer nodes represent LAFs. In this layer, an educator may add as many LAFs as he/she wishes. For sake of space in this paper we make use of five nodes Ci, i=33, 34…, 37 that represent equivalent number of LAFs as they are in tables 6 and 7. Finally, the concepts Ci, i=38, 39, 40, 41 in the lower layer represent the four LSs, as they appear in Kolb's learning cycle.

Every concept in the first layer gets a value $V^0(C_i) \in \{0.25, 0.5, 0.75, 1.0\}$ according to their rank. For example, if for a random user the rank of the statement in decreasing order is {B,D,C,A}, the values assigned to the upper layer nodes will be $V^0(C_1)$=0.25, $V^0(C_2)$=1.0, $V^0(C_3)$=0.5, $V^0(C_4)$=0,75. The rank of the statement is resulted from the user's response in KLSI in combination with the FIAA application. For the rest of the nodes, in the middle and lower layers, the system assigns null values ($V^0(C_i)$ =0, for i=33, 34…41). The corresponding weights w_{ij} are described using linguistic variables. Initially, the system adapts weights from the linguistic values of causal relations in Fig. 4. For i=1,2,…,32 and j=33,…,37 (upper to middle layer) the weights in Fig.3. For i=33…37 and j=38…41 (middle to lower layer) the weights appear in Fig. 4.

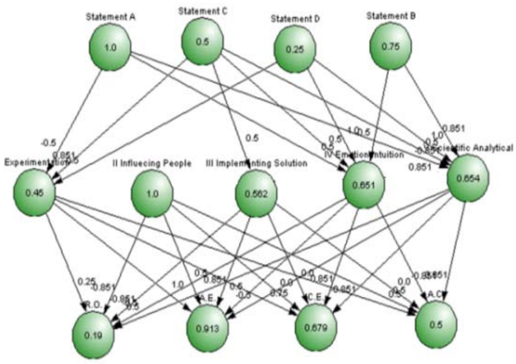

Fig. 3 3L-FCM Statements of one item in the upper layer, 5 LAFs in the middle layer and 4 Lss in the bottom layer.

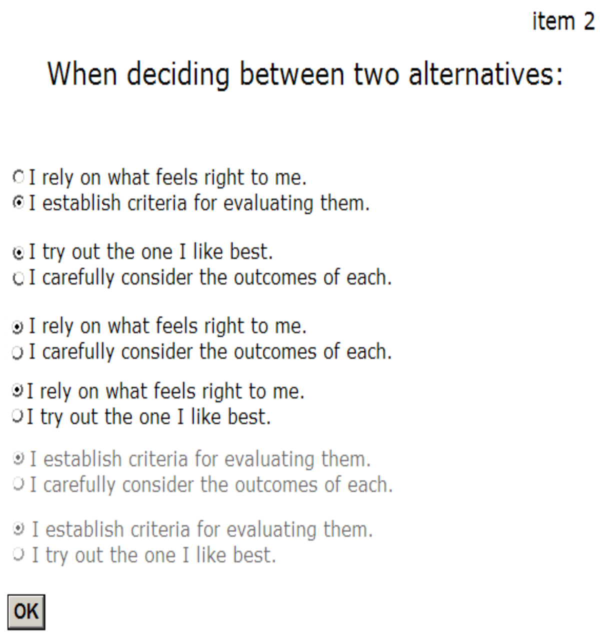

Fig. 4 Formal Representation of an item from Kolb's inventory. As soon as a rank of four items appears the FIAA does not allow any further responds to be given.

At the step n+1 the value $V^{n+1}(C_i)$ of the concept C_i is determined as in

$$V^{n+1}(C_i) = f\left(\sum_{\substack{j=1 \\ i \neq j}}^{41} w_{ji} V^n(C_j) \right) \tag{3}$$

where $V^n(C_i)$ is the value of concept C_i at the discrete time step n. As it has already been mentioned, the numerical values of weights have to lie in the interval [-1, 1].

They are the defuzzified values of the linguistic variables presented in Table III and Table IV.

TABLE III EXAMPLE OF FUZZY RELATIONS BETWEEN STATEMENTS A, B, C, D FROM KLSI(FIRST LAYER) AND LAFS (MIDDLE LAYER)

Statement	LAF	Linguistic Variable
A	Experimentation	Weak
	Influencing People	
	Implementing Solution	
	Emotion / Intuition	Strong
	Scientific / Analytic	Very weak
B	Experimentation	Weak
	Influencing People	
	Implementing Solution	
	Emotion / Intuition	Weak
	Scientific / Analytic	Very strong
C	Experimentation	Very strong
	Influencing People	
	Implementing Solution	Strong
	Emotion / Intuition	Strong
	Scientific / Analytic	Weak
D	Experimentation	Weak
	Influencing People	
	Implementing Solution	
	Emotion / Intuition	
	Scientific / Analytic	Very weak

TABLE IV EXAMPLE OF FUZZY RELATIONS BETWEEN LAF AND LS

LAF	LS	Linguistic Variable
Experimentation	Concrete experience	strong
	Reflective Observation	weak
	Abstract Conceptualization	normal
	Active Experimentation	very strong
Influencing People	Concrete experience	normal
	Reflective Observation	very weak
	Abstract Conceptualization	weak
	Active Experimentation	strong
Implementing Solution	Concrete experience	normal
	Reflective Observation	very weak
	Abstract Conceptualization	normal
	Active Experimentation	very strong
Emotion / Intuition	Concrete experience	very strong
	Reflective Observation	weak
	Abstract Conceptualization	very weak
	Active Experimentation	strong
Scientific / Analytic	Concrete experience	very weak
	Reflective Observation	strong
	Abstract Conceptualization	very strong
	Active Experimentation	weak

In this work the triangular membership function is used (Fig. 5).

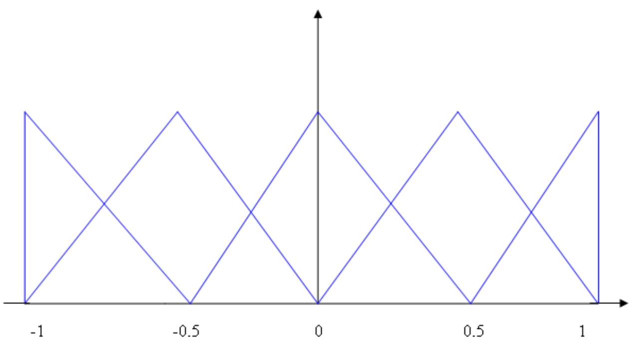

Fig. 5 Membership function

For this research we used a more general formulation

$$V^{n+1}(C_i) = f\left(k_1 \sum_{\substack{j=1 \\ i\neq j}}^{41} w_{ji} V^n(C_j) + k_2 V^n(C_i)\right) \tag{4}$$

Where $0 \le k1 \le 1$, $0 \le k2 \le 1$.

The coefficient k1 defines the concept's dependence on its interconnected concepts, while the coefficient k2 represent the proportion of contribution of the previous value of the concept in the computation of the new value. We selected k1=k2 =0.5 as this results in smoother variation of the values of the concepts after each recalculation and more discrete final values.

Educators may have personal opinions about the LS of learners. Especially, the presence of cultural diversity often arises the need of reconsider the relations between LAF and LSs. In such cases the teacher's point of view might be different from the system's output in what concerns certain learner(s). Whenever an educator disagrees with the system's outcomes, he/she may adjust the weights. To this end, the educator has to reconsider linguistic values of the weights. Also, the system maybe tuned simply by setting the final goals of LSs' estimation. Doing so, the Improved Nonlinear Hebbian Rule method's application adjusts weights automatically (Li & Shen, 2004). According this method a teacher provides random initial values for weights wji, regulates the Improved Nonlinear Hebbian Rule factors, which are n (learning rate), a (impulse parameter), e (goal) and k (iterations), as they appear in relation where

$$\Delta w_{ij}^{k} = a_k \Delta w_{ij}^{k-1} + n_k z_k^2 (1 - z_k)(V^k(C_i) - w_{ij}^{k-1} V^k(C_i))$$

$$z_k = \frac{1}{1 + e^{-V^k(C_i)}} \tag{5}$$

and re-educates the weights of the system in order to get the desired outcomes. The educated system functions for next users applying these weights. The method ends up with the k+1 iteration that satisfy the criterion $\left|V^{k+1}(C_i) - V^k(C_j)\right| < \varepsilon$ for a given small number ε.

B. Results

In the last stage of this work, an application of the proposed 3L-FCM has been installed. The application will be referred to as 3L-FCM Analyzer. It is a typical VB.NET application.

The application is based on a test group of 102 university's students. The students enrolled in an undergraduate Probability and Statistics course, volunteered to complete an on line KLSI. The test was applied at the beginning and the end of a semester to estimate test-retest reliability. In our previous work (Botsios, Georgiou, & Safouris, 2008) the collected results were used to supply with data the Bayesian Network that resulted LS diagnosis (BN).

In this work we use the very same responses as input data for the 3L-FCM Analyzer (Fig.6). The test-retest outcome was considered as metric variables LS (A) and LS (B) respectively. The collected responses served both as basis to compare with, and as database for the 3L-FCM Analyzer. Test-retest reliability was assessed using a Pearson LS(A)-LS(B) correlation, improved for the group given responses that produced outcomes through the proposed 3L-FCM LS

recognition model. As a matter of the 3L-FCM application, initially the weights of the system were decided according to theoretical relations given in Table Ⅲ and Table Ⅳ. A screenshot of the results page of 3L-FCM Analyzer is given in Fig. 6. The use of such weights resulted LS relative frequencies that appear in Fig. 7.

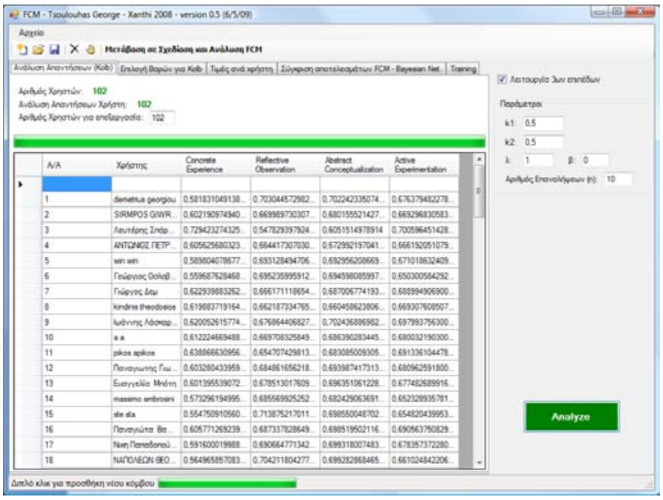

Fig. 6 Table of 3L- FCM Analyzer results assigned to each of 102 test group participants

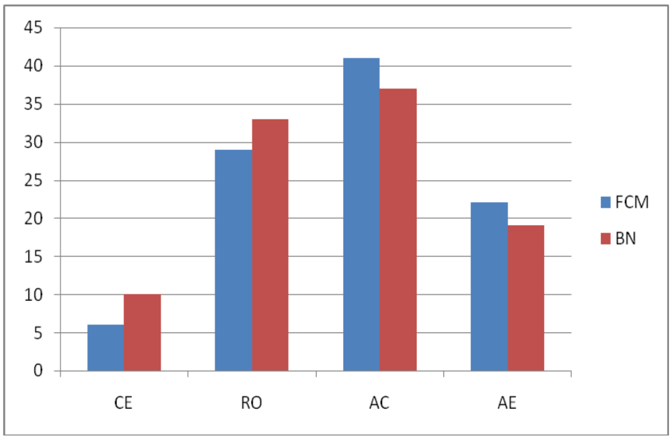

Fig. 7 LS Results with initial weights compared to BN

In Fig. 8 we present results gained from the 3L-FCM Analyzer followed an application of Improved Nonlinear Hebbian Rule with parameters α=0.1 n=0.1 and ε=0.001. Obviously they are closer to those of the BN application that those with initial weights.

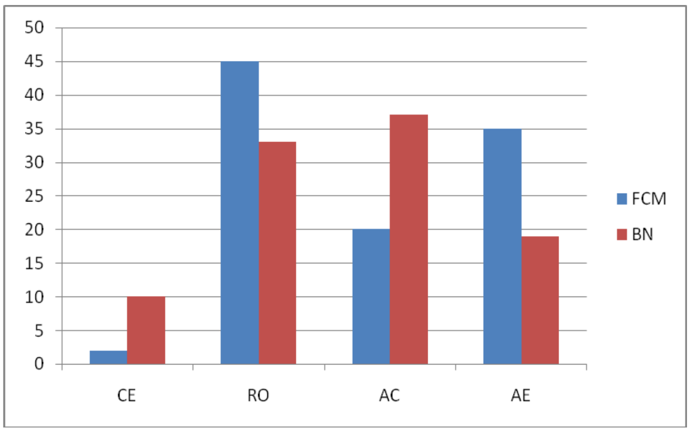

Fig. 8 LS results with improved nonlinear Hebbian rule compared to BN

II. CONCLUSIONS

A 3L FCM aiming to produce LS on line diagnosis, is presented. This schema has a basic innovative characteristic, that is its adjustability to various cognitive characteristics or learning abilities which may be expressed through the learner's LAFs. So, the proposed schema produces results (L.S. estimations) that can be modified in case of necessity (i.e. application on populations of cultural differences). Based on collected students' responses to the Kolb inventories, the proposed schema was tested. The resulted LS estimations were initially tuned, by changing the weights. This first attempt produced LS estimations very much alike to results gained in Botsios et. al. (2008). Recently, an application of the nonlinear Hebbian Rule drove to even better outcomes, i.e. L.S. estimations equally same to those appeared in Botsios et.al (2008).

Therefore, the main scope of this paper is to show that the proposed schema has the property of adjustability, avoiding any effort to convince that the experiments made on the small test group of 102 students lead to optimum diagnoses. The late is left to educators and cognitive scientists who may tune the system more properly.

Based on observations made on the test group of 102 university's students and using the Bayesian Network application (Botsios et al., 2008), it has been found that the each student's rank of responses can be classified into four leading classes Ci, i=1,2,3,4. Moreover, it has been observed that none of the classes corresponds to the same LS. For example, statement B appears to be the preferable choice for the majority of the students who has been recognized as AC. In Table 5, one can find related details.

TABLE V CORRELATION BETWEEN DOMINANT STATEMENTS AND LS

AC	0,070946	0,483108	0,239865	0,206081
AE	0,15	0,25	0,44375	0,15625
CE	0,306818	0,227273	0,284091	0,181818
RO	0,125	0,3125	0,1875	0,375

Figure 9 offers a graphical representation of the observed results.

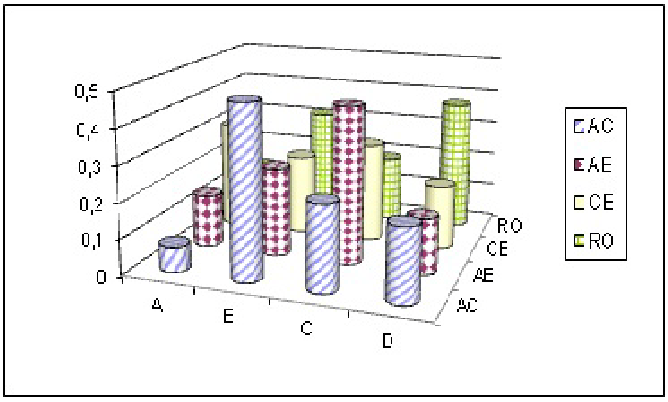

Fig. 9 Correlation between dominant statements and LS

The proposed scheme improves the results produced by the Bayesian network model for the reasons that: the stochastic models are based on statistical analysis and mainly refer to quantitative properties that are measurable. As far as LS and LAF are qualitative variables one needs to measure,

we have to consider rather fuzzy techniques than stochastic ones.

The 3L-FCM system requires no training period as a Bayesian model does.

1. A tutor has the ability to adjust the system using his/her experience on learners' LAF.
2. For the reasons 2 and 3 one can immediately implement the model in populations with different cultural backgrounds.
3. In addition, the proposed model is further adjustable with the help of dynamic Hebbian rule (in terms of certain parameters)
4. The authors of this paper believe that KLSI is designed in such a way that the majority of students, who respond preferring a certain statement in most of the items, are characterized with its corresponding LS. Therefore, one should look forward to further investigate restrictions for the weights, capable to preserve existing relations between statements A, B, C, D and LSs.

The problem of designing more efficient adjustable tools for LS diagnosis remains open as it is of great importance to AEHS. There are several points of view to look at in this problem. Nevertheless, research on this specific problem will contribute to the design of AEHS, taking advantage from various methods in applied mathematics and artificial intelligence.

The authors of this paper consider that it is on technology to prove the efficiency of cognitive theories, such as the impact of LS recognition on learning procedures. Web technologies and computers may serve as power tools to overcome the restrictions humans have in class. Computers will carry on the hard work accurately, with extremely high speed and repeatedly. They can provide us with huge portions of data from where we look forward to extract reliable information.

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REFERENCES

[1] ALI (2002a) Bracknell LEA November 2002. Inspection report. Coventry: Adult learning Inspectorate. Available via www.ali.gov.uk/

[2] ALI (2003b). Birmingham Institute of Education, Training, and Technology. February 2003. Inspection report. Coventry: Adult Learning Inspectorate. Available via: www.ali.gov.uk/

[3] Bajraktarevic, N., W. Hall, & P. Fullick (2003) ILASH: Incorporating Learning Strategies in Hypermedia. In Fourteenth Conference on Hypertext and Hypermedia.

[4] Berg, S. A., & S. Youn. (2008) Factors that influence informal learning in the workplace. Journal of Workplace Learning 20 (4):229-244.

[5] Botsios, S., D. Georgiou, & N. Safouris. (2008). Contributions to AEHS via on-line Learning Style Estimation. Journal of Educational Technology and Society 11 (2).

[6] Brown, E. J., & T. Brailsford. (2004). Integration of learning style theory in an adaptive educational hypermedia (AEH) system. In ALT-C Conference.

[7] Brusilovsky, P. (2001). Adaptive hypermedia. User Modelling and User-Adapted Interaction 11 (1-2).

[8] Carver, C.A., Howard, R.A., Lavelle, E., (1996) Enhancing student learning by incorporating student learning styles into adaptive hypermedia Proceedings of ED-MEDIA'96 - World Conference on Educational Multimedia and Hypermedia, Boston, MA pp. 118-123.

[9] Carver Jr, C. A., R. A. Howard, & W. D. Lane. (1999). Enhancing student learning through hypermedia courseware and incorporation of student learning styles. IEEE Transactions on Education 42 (1):33-38.

[10] Coffield, F., Moseley, D., Hall, E., Ecclestone, K. (2004) Should we be using learning styles? What recent research has to say to practice. London: Learning and Skills Research Centre

[11] Danielson, R., (1997) Learning styles, media preferences, and adaptive education, Proceedings of Workshop 'Adaptive Systems and User Modeling on the World Wide Web' at 6th International Conference on User Modeling, UM97, pp. 31-35.

[12] Dickerson, Julie A., & Bart Kosko. (1993). Virtual worlds as fuzzy cognitive maps. Paper read at 1993 IEEE Annual Virtual Reality International Symposium.

[13] Dunn, R., (1990) Rita Dunn answers questions on learning styles. Educational Leadership, 48(2) 15-19.

[14] Farnham-Diggory, Sylvia. (1992). The Learning- Disabled Child, Developing Child. Cambridge, MA: Harvard University Press.

[15] Felder, R. M., & L. K. Silverman. (1988). Learning and teaching styles in engineering education. Engineering Education 78 (7):674-681.

[16] Flouris, G. (1986). Architecture of Teaching and the procedure of learning. Athens: Gregory.

[17] Georgiou, D. A., & S. D. Botsios. (2008). Learning style recognition: A three layers fuzzy cognitive map schema. Proceedings of Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence). IEEE International Conference on Fuzzy Systems. art. no. 4630675, pp. 2202-2207.

[18] Georgopoulos, V. C., G. A. Malandraki, & C. D. Stylios. (2003). A fuzzy cognitive map approach to differential diagnosis of specific language impairment. Artificial Intelligence in Medicine 29 (3):261-278.

[19] Gilbert, J.E., Han, C.Y.Arthur: (1999) Adapting instruction to accommodate learning style, Proceedings of WebNet'99, World Conference of the WWW and Internet, pp. 433-438. Honolulu, HI.

[20] Graf, S., & Kinshuk. (2007). Considering Cognitive Traits and Learning Styles to Open Web-Based Learning to a Larger Student Community. In International Conference on Information and Communication Technology and Accessibility. Hammamet, Tunisia.

[21] Green, M. (2002) Improving initial assessment in work-based perspective. Theory into Practice. 23(1), 51-55.

[22] Honey P., & A. Mumford. (1992) The Manual of Learning Styles 3rd Ed. Maidenhead, Peter Honey.

[23] Honey, P., & A. Mumford. (2000). The Learning Styles Helper's Guide. Maidenhead: Peter Honey Publications.

[24] Huff, A. S. (1990). Mapping strategic thought, New York: Wiley.

[25] Hussein, B., & A. Ismael. (1995). Fuzzy neural network controller for a water desalination system. Proceedings of Artificial Neural Networks in Engineering (ANNIE'95):599-604.

[26] Joy S., Kolb D.A., Are There Cultural Differences in Learning Style? International Journal of Intercultural Relations, **33** (2009) 69-85.

[27] Jonassen D., Grabowski B., (1992) Handbook of individual differences learning and instruction Lawrence Erlbaum Associates.

[28] Ogbu J. U., (1992) Understanding Cultural Diversity and Learning, Educational Researcher, **21**, No 8., 5- 14+24.

[29] Kerawalla, L., S. Minocha, G. Kirkup, & G. Conole. (2009). An empirically grounded framework to guide blogging in higher education. Journal of Computer Assisted Learning 25 (1):31-42.

[30] Kolb, D., A (1999). The Kolb Learning Style Inventory. Version 3. Boston: Hay Group.

[31] Kolb, D. A. (1984). Experimental learning: Experience as the source of learning and development. Jersey: Prentice Hall.

[32] Lee, Kun Chang, Jin Sung Kim, Nam Ho Chung, & Soon Jae Kwon. (2002). Fuzzy cognitive map approach to web-mining inference amplification. Expert Systems with Applications 22 (3):197-211.

[33] Lee, S., & I. Han. (2000). Fuzzy cognitive map for the design of EDI controls. Information and Management 37 (1):37-50.

[34] Levy, Y. (2006). The top 10 most valuable online learning activities for graduate MIS students. International Journal of Information and Communication Technology Education 2 (3):27-44.

[35] Li, S. J., & R. M. Shen. (2004). Fuzzy cognitive map learning based on improved nonlinear hebbian rule. Paper read at Proceedings of 2004 International Conference on Machine Learning and Cybernetics.

[36] Liu Z. Q. (2001), Causation, Bayesian networks, and cognitive maps Zidnghua Xubao / Acta Automatica Sinica, Volume 27, Issue 4, Pages 552-566.

[37] Loo, R. (2004). Kolb's Learning Styles and Learning Preferences: Is there a linkage? Educational Psychology 24 (1):99-108.

[38] Loo, R., & K. Thorpe. (2000). Confirmatory factor analyses of the full and short versions of the Marlowe-Crowne social desirability scale. Journal of Social Psychology 140 (5):628-635.

[39] Manos, K. (1993). Educational Psychology - Psychopedagogy. Athens: Gregory.

[40] Mitropoulou, V. (2008). Educational Software for the Teaching of Religion in Schools. Thessaloniki: Vanias.

[41] Moore, A., T. J. Brailsford, & C. D. Stewart. (2001). Personally tailored teaching in WHURLE using conditional transclusion. In Proceedings of the ACM Conference on Hypertext.

[42] Osei-Bryson, K. M. (2004. Generating consistent subjective estimates of the magnitudes of causal relationships in fuzzy cognitive maps. Computers and Operations Research 31 (8):1165-1175.

[43] Papanikolaou, K. A., A. Mabbott, S. Bull, & M. Grigoriadou. (2006). Designing learner-controlled educational interactions based on learning/cognitive style and learner behaviour. Interacting with Computers 18 (3):356-384.

[44] Pipatsarun P., Jiracha V., (2010) Adaptive Intelligent Tutoring Systems for e-learning systems Procedia – Social and Behavioral Sciences, **2** (2) (2010) p.p. 4064-4069.

[45] Reynolds, M. (1997). Learning Styles: a critique. Management Learning. 28(2) 115-133.

[46] Specht, M., & R. Oppermann. (1998). ACE - adaptive courseware environment. New Review of Hypermedia and Multimedia 4:141-161.

[47] Stake, R. Learning parameters, aptitudes and achievements. Princeton Univ., Psychol. Dept., (1958). (multilith).

[48] Styblinski, M. A., & B. D. Meyer. (1988). Fuzzy cognitive maps, signal flow graphs, and qualitative circuit analysis. International Conference on Neural Networks, IEEE Issue 24-27 Vol. **2** page(s): 549 – 556.

[49] Verpoorten, D., M. Poumay, & D. Leclercq. (2007). The eight learning events model: A pedagogic conceptual tool supporting diversification of learning methods. Interactive Learning Environments 15 (2):151-160.

[50] Willcoxson, L., & M. Prosser. (1996). Kolb's Learning Style Inventory (1985): Review and further study of validity and reliability. British Journal of Educational Psychology 66 (2):247-257.

[51] Wolf, C. (2003). iWeaver: Towards 'Learning Style'-based e-Learning in Computer Science Education. In Proceedings of the Fifth Australasian Computing Education Conference on Computing Education 2003.

[52] Yahya, I. (1998). Willcoxson & Prosser's factor analyses on Kolb's (1985) LSI data: Reflections and re-analyses. British Journal of Educational Psychology 68 (2):281-286.